Store_Sales_Forecast

March 6, 2022

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.deterministic import CalendarFourier, DeterministicProcess
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.stattools import adfuller
from scipy.signal import periodogram
from scipy.stats.mstats import normaltest
from sklearn.model_selection import train_test_split, RandomizedSearchCV,␣
↪GridSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.multioutput import MultiOutputRegressor
from xgboost import XGBRegressor
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.pipeline import Pipeline
import tensorflow as tf
import keras
from livelossplot import PlotLossesKeras
from warnings import simplefilter
simplefilter("ignore")
# Set Matplotlib defaults
#plt.style.use("seaborn-whitegrid")
plt.style.use('ggplot')
plt.rc("figure", autolayout=True, figsize=(11, 5))
plt.rc("axes", labelweight="bold", labelsize="large", titleweight="bold",␣
↪titlesize=16, titlepad=10)
plot_params = dict(color="0.75", style=".-", markeredgecolor="0.25",␣
↪markerfacecolor="0.25", legend=False)
%config InlineBackend.figure_format = 'retina'
np.random.seed(42)
```

[2]:
```
def seasonal_plot(X, y, period, freq, ax=None):
    if ax is None:
        _, ax = plt.subplots()
    palette = sns.color_palette("husl", n_colors=X[period].nunique(),)
    ax = sns.lineplot(x=freq, y=y, hue=period, data=X, ci=False, ax=ax,␣
↪palette=palette, legend=False)
    ax.set_title(f"Seasonal Plot ({period}/{freq})")
    for line, name in zip(ax.lines, X[period].unique()):
        y_ = line.get_ydata()[-1]
        ax.annotate(name, xy=(1, y_), xytext=(6, 0), color=line.get_color(),␣
↪xycoords=ax.get_yaxis_transform(),
                    textcoords="offset points", size=14, va="center")
    return ax


def plot_periodogram(ts, detrend='linear', ax=None):
    from scipy.signal import periodogram
    fs = pd.Timedelta("1Y") / pd.Timedelta("1D")
    freqencies, spectrum = periodogram(ts, fs=fs, detrend=detrend,␣
↪window="boxcar", scaling='spectrum')
    if ax is None:
        _, ax = plt.subplots()
    ax.step(freqencies, spectrum, color="purple")
    ax.set_xscale("log")
    ax.set_xticks([1, 2, 4, 6, 12, 26, 52, 104])
    ax.set_xticklabels(["Annual (1)", "Semiannual (2)", "Quarterly (4)",␣
↪"Bimonthly (6)", "Monthly (12)",
                        "Biweekly (26)", "Weekly (52)", "Semiweekly (104)"],␣
↪rotation=30)
    ax.ticklabel_format(axis="y", style="sci", scilimits=(0, 0))
    ax.set_ylabel("Variance")
    ax.set_title("Periodogram")
    return ax

def lagplot(x, y=None, lag=1, standardize=False, ax=None, **kwargs):
    from matplotlib.offsetbox import AnchoredText
    x_ = x.shift(lag)
    if standardize:
        x_ = (x_ - x_.mean()) / x_.std()
    if y is not None:
        y_ = (y - y.mean()) / y.std() if standardize else y
    else:
        y_ = x
    corr = y_.corr(x_)
    if ax is None:
        fig, ax = plt.subplots()
    scatter_kws = dict(alpha=0.75, s=3)
```

```
    line_kws = dict(color='C3', )
    ax = sns.regplot(x=x_, y=y_, scatter_kws=scatter_kws, line_kws=line_kws, lowess=True, ax=ax, **kwargs)
    at = AnchoredText(f"{corr:.2f}", prop=dict(size="large"), frameon=True, loc="upper left")
    at.patch.set_boxstyle("square, pad=0.0")
    ax.add_artist(at)
    ax.set(title=f"Lag {lag}", xlabel=x_.name, ylabel=y_.name)
    return ax


def plot_lags(x, y=None, lags=6, nrows=1, lagplot_kwargs={}, **kwargs):
    import math
    kwargs.setdefault('nrows', nrows)
    kwargs.setdefault('ncols', math.ceil(lags / nrows))
    kwargs.setdefault('figsize', (kwargs['ncols'] * 2, nrows * 2 + 0.5))
    fig, axs = plt.subplots(sharex=True, sharey=True, squeeze=False, **kwargs)
    for ax, k in zip(fig.get_axes(), range(kwargs['nrows'] * kwargs['ncols'])):
        if k + 1 <= lags:
            ax = lagplot(x, y, lag=k + 1, ax=ax, **lagplot_kwargs)
            ax.set_title(f"Lag {k + 1}", fontdict=dict(fontsize=14))
            ax.set(xlabel="", ylabel="")
        else:
            ax.axis('off')
    plt.setp(axs[-1, :], xlabel=x.name)
    plt.setp(axs[:, 0], ylabel=y.name if y is not None else x.name)
    fig.tight_layout(w_pad=0.1, h_pad=0.1)
    return fig

# define train test split function
def train_test_datasets(df, x_len=12, y_len=1, test_loops=12):
    D = df.values
    rows, periods = D.shape

    # Training set creation
    loops = periods + 1 - x_len - y_len
    train = []
    for col in range(loops):
        train.append(D[:, col:col+x_len+y_len])
    train = np.vstack(train)
    X_train, y_train = np.split(train, [-y_len], axis=1)

    # Test set creation
    if test_loops > 0:
        X_train, X_test = np.split(X_train, [-rows*test_loops], axis=0)
        y_train, y_test = np.split(y_train, [-rows*test_loops], axis=0)
    else: # No test set: X_test is used to generate the future forecast
```

```
        X_test = D[:, -x_len:]
        y_test = np.full((X_test.shape[0], y_len), np.nan) #Dummy value

    # Formatting required for scikit-learn
    if y_len == 1:
        y_train = y_train.ravel()
        y_test = y_test.ravel()

    return X_train, y_train, X_test, y_test

# define score metric function
def kpi(y_train, y_train_pred, y_test, y_test_pred, name=''):
    df = pd.DataFrame(columns = ['MAE','RMSE', 'Bias', 'MAE_pct', 'RMSE_pct',␣
 ↪'r2_score'], index=['Train','Test'])
    df.index.name = name
    df.loc['Train','MAE_pct'] = 100*np.mean(abs(y_train - y_train_pred))/np.
 ↪mean(y_train)
    df.loc['Train','RMSE_pct'] = 100*np.sqrt(np.mean((y_train -␣
 ↪y_train_pred)**2))/np.mean(y_train)
    df.loc['Train','Bias'] = 100*np.mean((y_train - y_train_pred))/np.
 ↪mean(y_train)
    df.loc['Train','r2_score'] =  r2_score(y_train, y_train_pred)
    df.loc['Train','MAE'] = mean_absolute_error(y_train, y_train_pred)
    df.loc['Train','RMSE'] = mean_squared_error(y_train, y_train_pred,␣
 ↪squared=False)
    df.loc['Test','MAE_pct'] = 100*np.mean(abs(y_test - y_test_pred))/np.
 ↪mean(y_test)
    df.loc['Test','RMSE_pct'] = 100*np.sqrt(np.mean((y_test - y_test_pred)**2))/
 ↪np.mean(y_test)
    df.loc['Test','Bias'] = 100*np.mean((y_test - y_test_pred))/np.mean(y_test)
    df.loc['Test','r2_score'] =  r2_score(y_test, y_test_pred)
    df.loc['Test','MAE'] = mean_absolute_error(y_test, y_test_pred)
    df.loc['Test','RMSE'] = mean_squared_error(y_test, y_test_pred,␣
 ↪squared=False)
    df = df.astype(float).round(2) #Round number for display
    print(df)
```

[3]:
```
data = pd.read_csv('train.csv')
data.head()
```

[3]:

	id	date	store_nbr	family	sales	onpromotion
0	0	2013-01-01	1	AUTOMOTIVE	0.0	0
1	1	2013-01-01	1	BABY CARE	0.0	0
2	2	2013-01-01	1	BEAUTY	0.0	0
3	3	2013-01-01	1	BEVERAGES	0.0	0
4	4	2013-01-01	1	BOOKS	0.0	0

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000888 entries, 0 to 3000887
Data columns (total 6 columns):
 #   Column       Dtype
---  ------       -----
 0   id           int64
 1   date         object
 2   store_nbr    int64
 3   family       object
 4   sales        float64
 5   onpromotion  int64
dtypes: float64(1), int64(3), object(2)
memory usage: 137.4+ MB
```

[5]:
```
data.date = pd.to_datetime(data.date)
```

[6]:
```
dframe = pd.pivot_table(data=data, values='sales', index='date',␣
 ↪columns='family', aggfunc='sum', fill_value=0)
dframe.head()
```

[6]:
```
family      AUTOMOTIVE  BABY CARE  BEAUTY  BEVERAGES  BOOKS  BREAD/BAKERY  \
date
2013-01-01           0          0       2        810      0     180.58900
2013-01-02         255          0     207      72092      0   26246.31900
2013-01-03         161          0     125      52105      0   18456.48002
2013-01-04         169          0     133      54167      0   16721.96901
2013-01-05         342          0     191      77818      0   22367.76108

family      CELEBRATION  CLEANING  DAIRY         DELI  …  MAGAZINES  \
date                                                   …
2013-01-01            0       186    143     71.09000  …          0
2013-01-02            0     74629  23381  15754.50000  …          0
2013-01-03            0     55893  18001  11172.45500  …          0
2013-01-04            0     52064  18148  10143.20900  …          0
2013-01-05            0     70128  23082  13734.94501  …          0

family             MEATS  PERSONAL CARE  PET SUPPLIES  \
date
2013-01-01    110.801000             25             0
2013-01-02  20871.464028          17204             0
2013-01-03  16597.398113          12568             0
2013-01-04  21625.963055          11303             0
2013-01-05  20879.091050          16819             0

family      PLAYERS AND ELECTRONICS       POULTRY  PREPARED FOODS  PRODUCE  \
```

```
date
2013-01-01                        0     42.637000      37.847000      0.0
2013-01-02                        0  13975.884938    5338.111976      0.0
2013-01-03                        0  10674.393983    3591.388005      0.0
2013-01-04                        0  10772.515038    4472.965990      0.0
2013-01-05                        0  13475.009055    5830.073020      0.0

family      SCHOOL AND OFFICE SUPPLIES      SEAFOOD
date
2013-01-01                           0     0.000000
2013-01-02                           0  1526.750002
2013-01-03                           0  1094.310994
2013-01-04                           0  1293.120995
2013-01-05                           0  1245.637004

[5 rows x 33 columns]
```

[8]:
```python
dframe.shape
```

[8]:
```
(1684, 33)
```

[9]:
```python
# check missing dates

index = pd.date_range(start=dframe.index.min(), end='2017-08-15', freq='D')
print('number of missing dates = ', index.shape[0] - dframe.shape[0])
```

```
number of missing dates =  4
```

[10]:
```python
index
```

[10]:
```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10',
               …
               '2017-08-06', '2017-08-07', '2017-08-08', '2017-08-09',
               '2017-08-10', '2017-08-11', '2017-08-12', '2017-08-13',
               '2017-08-14', '2017-08-15'],
              dtype='datetime64[ns]', length=1688, freq='D')
```

[11]:
```python
dframe = dframe.reindex(index)
dframe.tail()
```

[11]:
```
family      AUTOMOTIVE  BABY CARE  BEAUTY  BEVERAGES  BOOKS  BREAD/BAKERY  \
2017-08-11       441.0        7.0   351.0   189111.0    0.0   28204.48600
2017-08-12       403.0        3.0   369.0   182318.0    0.0   27403.54800
2017-08-13       481.0        9.0   433.0   202354.0    1.0   33262.75700
2017-08-14       292.0        9.0   337.0   174832.0    0.0   28002.45700
```

```
2017-08-15       337.0        8.0   339.0   170773.0    0.0   29158.19502

family       CELEBRATION  CLEANING    DAIRY          DELI  …  MAGAZINES  \
2017-08-11         870.0   55682.0  44909.0  18680.488004  …      500.0
2017-08-12         849.0   57935.0  42854.0  15689.893010  …      483.0
2017-08-13         544.0   61757.0  50112.0  17593.274020  …      469.0
2017-08-14         594.0   55032.0  43050.0  14662.741000  …      457.0
2017-08-15         597.0   58474.0  40707.0  14935.453000  …      461.0

family              MEATS  PERSONAL CARE  PET SUPPLIES  \
2017-08-11  26944.092010        15978.0         587.0
2017-08-12  17775.650112        15903.0         508.0
2017-08-13  18633.015039        18188.0         541.0
2017-08-14  16975.686040        15077.0         417.0
2017-08-15  17928.170944        14787.0         364.0

family      PLAYERS AND ELECTRONICS       POULTRY  PREPARED FOODS  \
2017-08-11                    654.0  25318.297990     5199.494021
2017-08-12                    712.0  19134.510058     4573.465992
2017-08-13                    741.0  20509.265004     4941.509018
2017-08-14                    500.0  18597.508060     4647.375002
2017-08-15                    592.0  17586.709986     4641.522980

family           PRODUCE  SCHOOL AND OFFICE SUPPLIES      SEAFOOD
2017-08-11  118738.14300                      3523.0  1272.615997
2017-08-12  111788.35090                      3644.0  1028.030006
2017-08-13  125923.80240                      3718.0  1118.047000
2017-08-14  115257.59598                      2826.0   970.679999
2017-08-15  125108.97100                      2530.0   970.177005

[5 rows x 33 columns]
```

[12]:
```
dframe.isnull().sum()
```

[12]:
```
family
AUTOMOTIVE                    4
BABY CARE                     4
BEAUTY                        4
BEVERAGES                     4
BOOKS                         4
BREAD/BAKERY                  4
CELEBRATION                   4
CLEANING                      4
DAIRY                         4
DELI                          4
EGGS                          4
FROZEN FOODS                  4
```

```
GROCERY I                     4
GROCERY II                    4
HARDWARE                      4
HOME AND KITCHEN I            4
HOME AND KITCHEN II           4
HOME APPLIANCES               4
HOME CARE                     4
LADIESWEAR                    4
LAWN AND GARDEN               4
LINGERIE                      4
LIQUOR,WINE,BEER              4
MAGAZINES                     4
MEATS                         4
PERSONAL CARE                 4
PET SUPPLIES                  4
PLAYERS AND ELECTRONICS       4
POULTRY                       4
PREPARED FOODS                4
PRODUCE                       4
SCHOOL AND OFFICE SUPPLIES    4
SEAFOOD                       4
dtype: int64
```

[13]:
```
dframe.fillna(0, inplace=True)
dframe.head()
```

[13]:
```
family      AUTOMOTIVE  BABY CARE  BEAUTY  BEVERAGES  BOOKS  BREAD/BAKERY  \
2013-01-01         0.0        0.0     2.0      810.0    0.0     180.58900
2013-01-02       255.0        0.0   207.0    72092.0    0.0   26246.31900
2013-01-03       161.0        0.0   125.0    52105.0    0.0   18456.48002
2013-01-04       169.0        0.0   133.0    54167.0    0.0   16721.96901
2013-01-05       342.0        0.0   191.0    77818.0    0.0   22367.76108

family      CELEBRATION  CLEANING    DAIRY         DELI  …  MAGAZINES  \
2013-01-01          0.0     186.0    143.0     71.09000  …        0.0
2013-01-02          0.0   74629.0  23381.0  15754.50000  …        0.0
2013-01-03          0.0   55893.0  18001.0  11172.45500  …        0.0
2013-01-04          0.0   52064.0  18148.0  10143.20900  …        0.0
2013-01-05          0.0   70128.0  23082.0  13734.94501  …        0.0

family             MEATS  PERSONAL CARE  PET SUPPLIES  \
2013-01-01    110.801000           25.0           0.0
2013-01-02  20871.464028        17204.0           0.0
2013-01-03  16597.398113        12568.0           0.0
2013-01-04  21625.963055        11303.0           0.0
2013-01-05  20879.091050        16819.0           0.0
```

```
family      PLAYERS AND ELECTRONICS       POULTRY  PREPARED FOODS  PRODUCE  \
2013-01-01                      0.0     42.637000       37.847000      0.0
2013-01-02                      0.0  13975.884938     5338.111976      0.0
2013-01-03                      0.0  10674.393983     3591.388005      0.0
2013-01-04                      0.0  10772.515038     4472.965990      0.0
2013-01-05                      0.0  13475.009055     5830.073020      0.0

family      SCHOOL AND OFFICE SUPPLIES      SEAFOOD
2013-01-01                         0.0     0.000000
2013-01-02                         0.0  1526.750002
2013-01-03                         0.0  1094.310994
2013-01-04                         0.0  1293.120995
2013-01-05                         0.0  1245.637004

[5 rows x 33 columns]
```

[14]:
```
dframe.isnull().sum()
```

[14]:
```
family
AUTOMOTIVE                    0
BABY CARE                     0
BEAUTY                        0
BEVERAGES                     0
BOOKS                         0
BREAD/BAKERY                  0
CELEBRATION                   0
CLEANING                      0
DAIRY                         0
DELI                          0
EGGS                          0
FROZEN FOODS                  0
GROCERY I                     0
GROCERY II                    0
HARDWARE                      0
HOME AND KITCHEN I            0
HOME AND KITCHEN II           0
HOME APPLIANCES               0
HOME CARE                     0
LADIESWEAR                    0
LAWN AND GARDEN               0
LINGERIE                      0
LIQUOR,WINE,BEER              0
MAGAZINES                     0
MEATS                         0
PERSONAL CARE                 0
PET SUPPLIES                  0
PLAYERS AND ELECTRONICS       0
```

```
POULTRY                       0
PREPARED FOODS                0
PRODUCE                       0
SCHOOL AND OFFICE SUPPLIES    0
SEAFOOD                       0
dtype: int64
```

[15]:
```python
df = dframe.T
df.head()
```

[15]:
```
            2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  \
family
AUTOMOTIVE         0.0       255.0       161.0       169.0       342.0
BABY CARE          0.0         0.0         0.0         0.0         0.0
BEAUTY             2.0       207.0       125.0       133.0       191.0
BEVERAGES        810.0     72092.0     52105.0     54167.0     77818.0
BOOKS              0.0         0.0         0.0         0.0         0.0

            2013-01-06  2013-01-07  2013-01-08  2013-01-09  2013-01-10  …  \
family                                                                  …
AUTOMOTIVE       360.0       189.0       229.0       164.0       164.0  …
BABY CARE          0.0         0.0         0.0         0.0         0.0  …
BEAUTY           265.0       124.0       116.0       104.0        96.0  …
BEVERAGES      86184.0     51619.0     46941.0     47910.0     42390.0  …
BOOKS              0.0         0.0         0.0         0.0         0.0  …

            2017-08-06  2017-08-07  2017-08-08  2017-08-09  2017-08-10  \
family
AUTOMOTIVE       583.0       355.0       327.0       314.0       313.0
BABY CARE         16.0        14.0         5.0        10.0         5.0
BEAUTY           558.0       317.0       328.0       315.0       309.0
BEVERAGES     250784.0    179419.0    160636.0    153010.0    156449.0
BOOKS              1.0         0.0         1.0         2.0         0.0

            2017-08-11  2017-08-12  2017-08-13  2017-08-14  2017-08-15
family
AUTOMOTIVE       441.0       403.0       481.0       292.0       337.0
BABY CARE          7.0         3.0         9.0         9.0         8.0
BEAUTY           351.0       369.0       433.0       337.0       339.0
BEVERAGES     189111.0    182318.0    202354.0    174832.0    170773.0
BOOKS              0.0         0.0         1.0         0.0         0.0

[5 rows x 1688 columns]
```

[16]:
```python
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=365, y_len=1,␣
    ↪test_loops=150)
```

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[16]: ((38709, 365), (4950, 365), (38709,), (4950,))

[17]:
```
# Linear Regression as first model to compare

reg = Pipeline([('scaler', StandardScaler()), ('poly', PolynomialFeatures(1)),
                ('LinearRegression', LinearRegression())]) # Create a linear␣
↪regression object


reg.fit(X_train, y_train) # Fit it to the training data

# Create two predictions for the training and test sets
y_train_pred = reg.predict(X_train)
y_test_pred = reg.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='Regression')
```

```
                MAE     RMSE  Bias  MAE_pct  RMSE_pct  r2_score
Regression
Train       2192.28  7563.83 -0.00    10.55     36.40      0.98
Test        2984.20  8990.38 -0.66    11.46     34.54      0.98
```

[18]:
```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=365, y_len=1,␣
↪test_loops=0) #use 252 for 1day, 253 for second day

reg = Pipeline([('scaler', StandardScaler()), ('poly', PolynomialFeatures(1)),
                ('LinearRegression', LinearRegression())]) # Create a linear␣
↪regression object

reg.fit(X_train,y_train) # Fit it to the training data

reg_forecast = pd.DataFrame(data=reg.predict(X_test), index=df.index)#,␣
↪columns=['21-02-2022', '22-02-2022'])
reg_forecast.head()
```

[18]:
```
                        0
family
AUTOMOTIVE     398.222656
BABY CARE       72.894531
BEAUTY         421.585938
BEVERAGES   157857.492188
BOOKS           52.519531
```

[20]:
```
# use Random Forest with default parameters

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=7, y_len=1,␣
↪test_loops=150)

forest = Pipeline([('scaler', MinMaxScaler()), ('Forest',␣
↪RandomForestRegressor())])

forest.fit(X_train, y_train)

y_train_pred = forest.predict(X_train)
y_test_pred = forest.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='Forest')
```

```
             MAE     RMSE  Bias  MAE_pct  RMSE_pct  r2_score
Forest
Train     684.12  3022.21 -0.03     3.67     16.21      1.00
Test     2493.39  8960.10  0.66     9.58     34.42      0.98
```

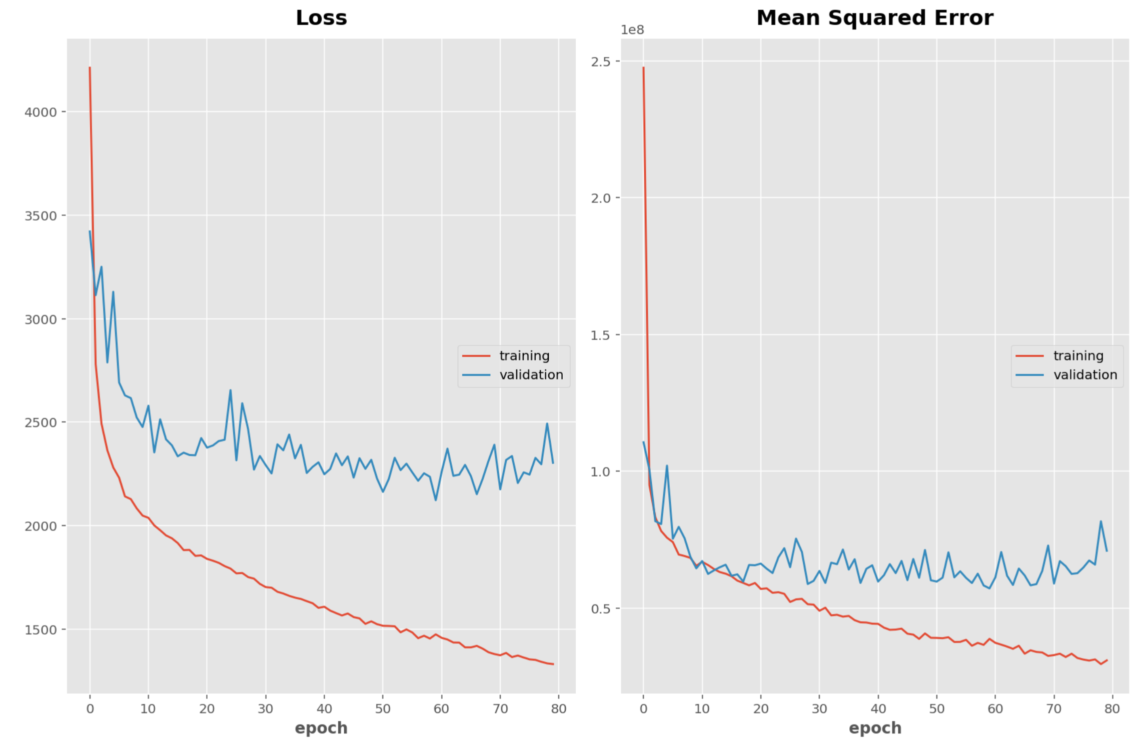
0.0.1 LSTM

[21]:
```
x_len = 7
y_len = 1
n_features = 1

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=x_len,␣
↪y_len=y_len, test_loops=150)

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# reshape from [samples, timesteps] into [samples, timesteps, features]
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))
y_train = y_train.reshape(X_train.shape[0], y_len)
y_test = y_test.reshape(X_test.shape[0], y_len)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[21]:
```
((50523, 7, 1), (4950, 7, 1), (50523, 1), (4950, 1))
```

[22]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)
```

```
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0,␣
 ↪patience=20, verbose=0, mode='auto')

model = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=96,
                                                          kernel_size=5,
                                                          strides=1,
                                                          padding='causal',
                                                          activation='relu',
                                                          input_shape=(x_len,␣
 ↪n_features)),
                                    tf.keras.layers.LSTM(100,␣
 ↪return_sequences=True),
                                    tf.keras.layers.LSTM(100),
                                    tf.keras.layers.Dense(30),
                                    tf.keras.layers.Dense(10),
                                    tf.keras.layers.Dense(y_len),
                                    tf.keras.layers.Lambda(lambda x: x * 400)])


#model.compile(loss='mean_squared_error',optimizer='adam')

model.compile(loss=tf.keras.losses.Huber() ,optimizer='adam', metrics=['mse'])

history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
 ↪epochs=500,
                    callbacks=[PlotLossesKeras(), callback], verbose=1)
```




```
Loss
        training                (min: 1330.752, max: 4212.436, cur: 1330.752)
        validation              (min: 2122.604, max: 3421.258, cur: 2303.420)
Mean Squared Error
        training                (min: 29506994.000, max: 247435360.000, cur:
30862612.000)
        validation              (min: 57162392.000, max: 110578752.000, cur:
70923736.000)
1579/1579 [==============================] - 22s 14ms/step - loss: 1330.7518 -
mse: 30862612.0000 - val_loss: 2303.4202 - val_mse: 70923736.0000
```

[23]:
```python
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='LSTM')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
LSTM						
Train	1291.66	5352.72	1.55	6.93	28.70	0.99
Test	2303.92	8421.62	2.17	8.85	32.35	0.98

[24]:
```python
# Forecasting

x_len = 7
```

```
y_len = 1
n_features = 1

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=x_len,␣
 ↪y_len=y_len, test_loops=0)

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# reshape from [samples, timesteps] into [samples, timesteps, features]
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))
y_train = y_train.reshape(X_train.shape[0], y_len)
y_test = y_test.reshape(X_test.shape[0], y_len)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[24]: ((55473, 7, 1), (33, 7, 1), (55473, 1), (33, 1))

[25]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)

#callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0,␣
 ↪patience=20, verbose=0, mode='auto')

model = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=96,
                                                           kernel_size=5,
                                                           strides=1,
                                                           padding='causal',
                                                           activation='relu',
                                                           input_shape=(x_len,␣
 ↪n_features)),
                                    tf.keras.layers.LSTM(100,␣
 ↪return_sequences=True),
                                    tf.keras.layers.LSTM(100),
                                    tf.keras.layers.Dense(30),
                                    tf.keras.layers.Dense(10),
                                    tf.keras.layers.Dense(y_len),
                                    tf.keras.layers.Lambda(lambda x: x * 400)])


#model.compile(loss='mean_squared_error',optimizer='adam')

model.compile(loss=tf.keras.losses.Huber() ,optimizer='adam', metrics=['mse'])
```

```
history = model.fit(X_train, y_train, epochs=100, verbose=0)
```

[26]:
```
forecast = pd.DataFrame(data=model.predict(X_test), index=df.index,␣
 ↪columns=['Next_Sales'])
forecast.head()
```

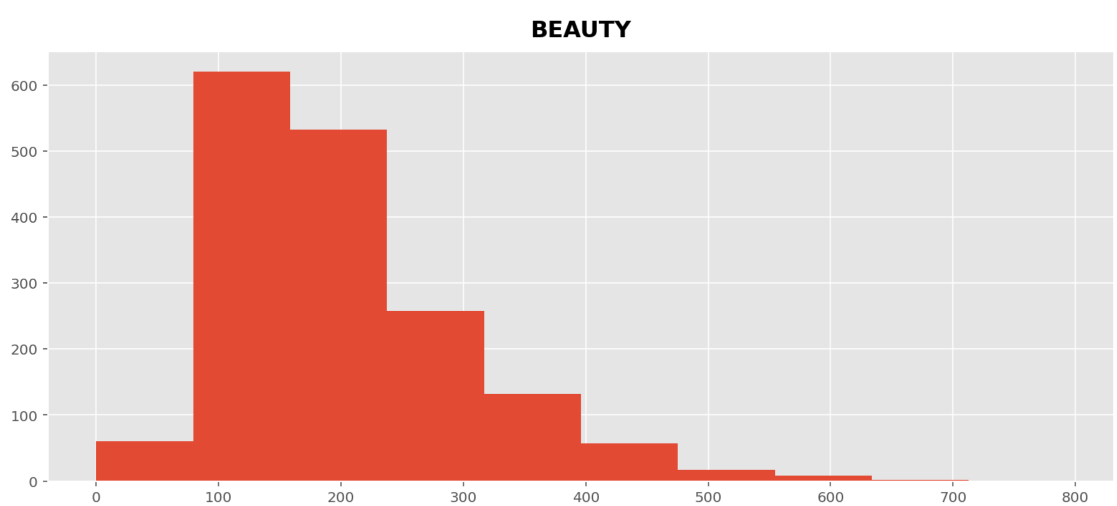
[26]:
```
                 Next_Sales
family
AUTOMOTIVE       338.813416
BABY CARE         30.125034
BEAUTY           337.277069
BEVERAGES     151871.812500
BOOKS             23.183649
```

0.1 Single Forecast Beauty from the store

[167]:
```
df = dframe.loc[:, ['BEAUTY']]
df.head()
```

[167]:
```
family      BEAUTY
2013-01-01     2.0
2013-01-02   207.0
2013-01-03   125.0
2013-01-04   133.0
2013-01-05   191.0
```

[168]:
```
df.hist();
```



[169]:
```
df = np.log(df+1)
df
```

[169]:
```
family         BEAUTY
2013-01-01  1.098612
2013-01-02  5.337538
2013-01-03  4.836282
2013-01-04  4.897840
2013-01-05  5.257495
…                …
2017-08-11  5.863631
2017-08-12  5.913503
2017-08-13  6.073045
2017-08-14  5.823046
2017-08-15  5.828946

[1688 rows x 1 columns]
```

[170]:
```
df.min()
```

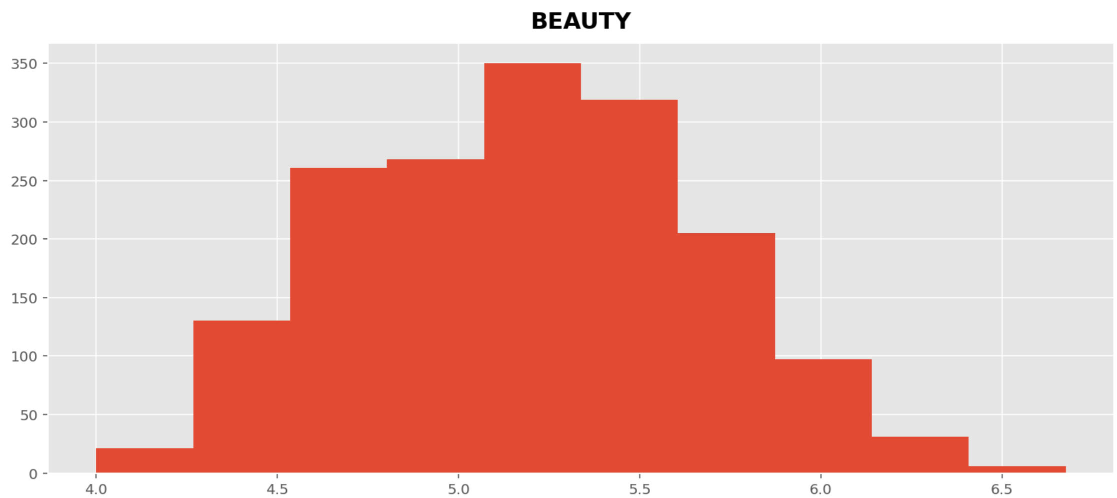
[170]:
```
family
BEAUTY    0.0
dtype: float64
```

[174]:
```
q = np.quantile(df, 0.1)
q
```

[174]:
```
4.561206801507648
```

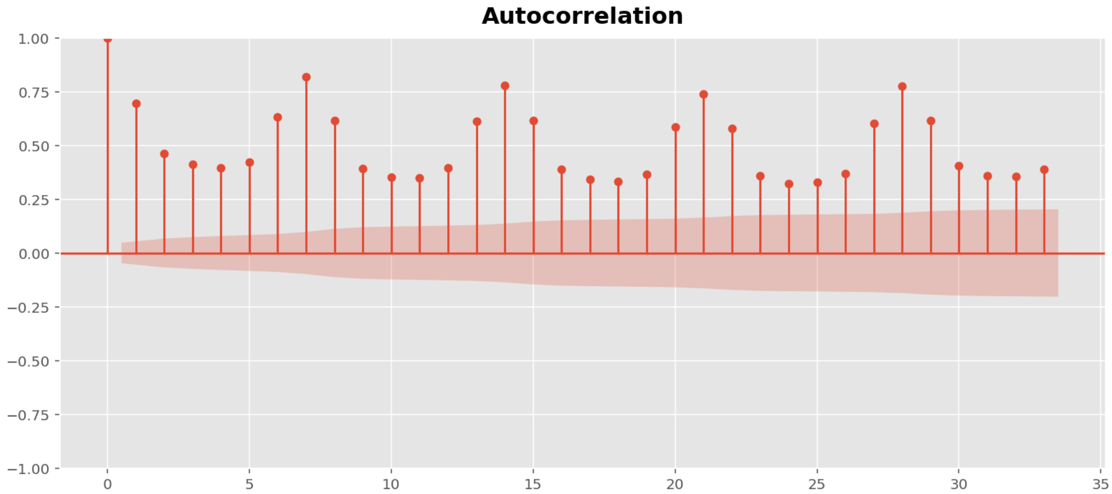
[175]:
```
df[df<4] = 4
```

[176]:
```
df.hist();
```



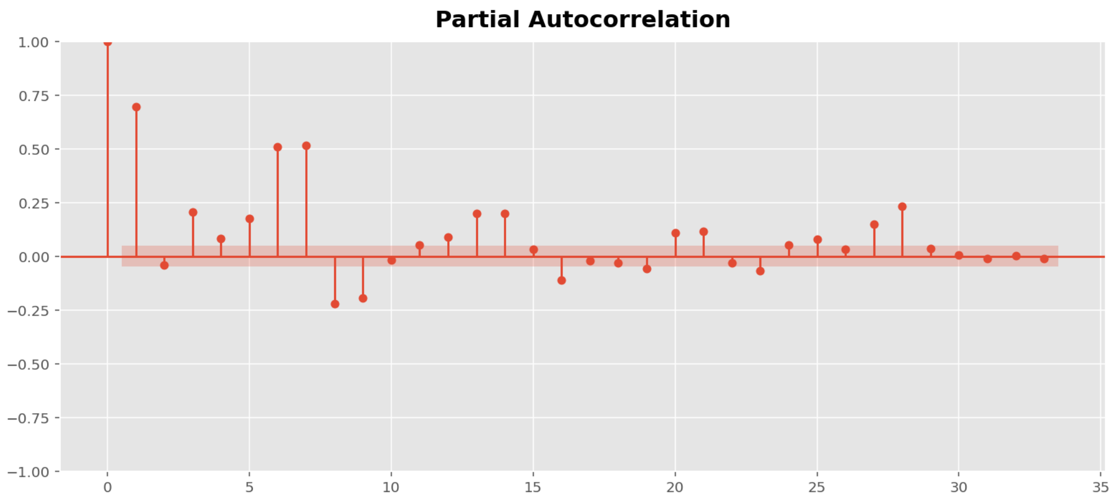
[177]:

```
plot_acf(df);
```



[178]:

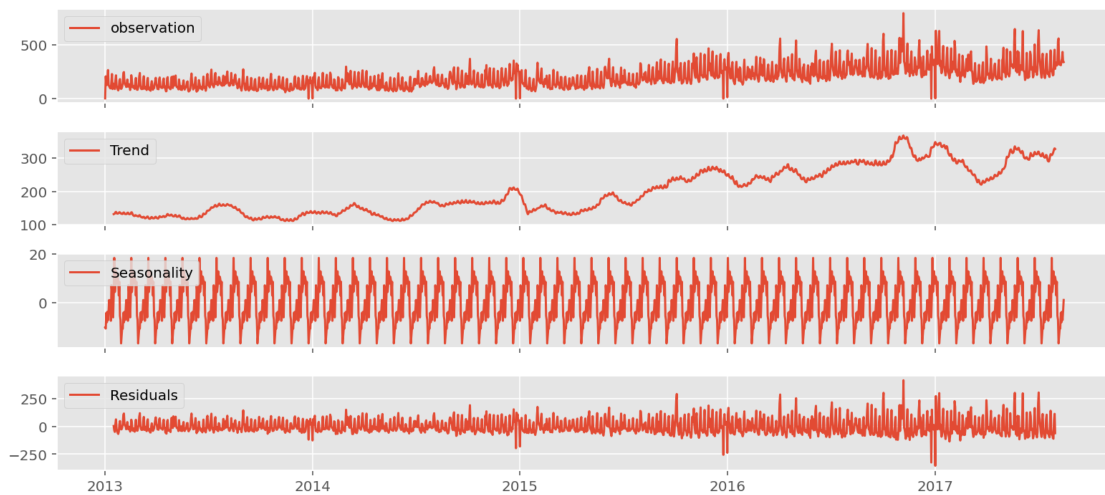
```
plot_pacf(df);
```



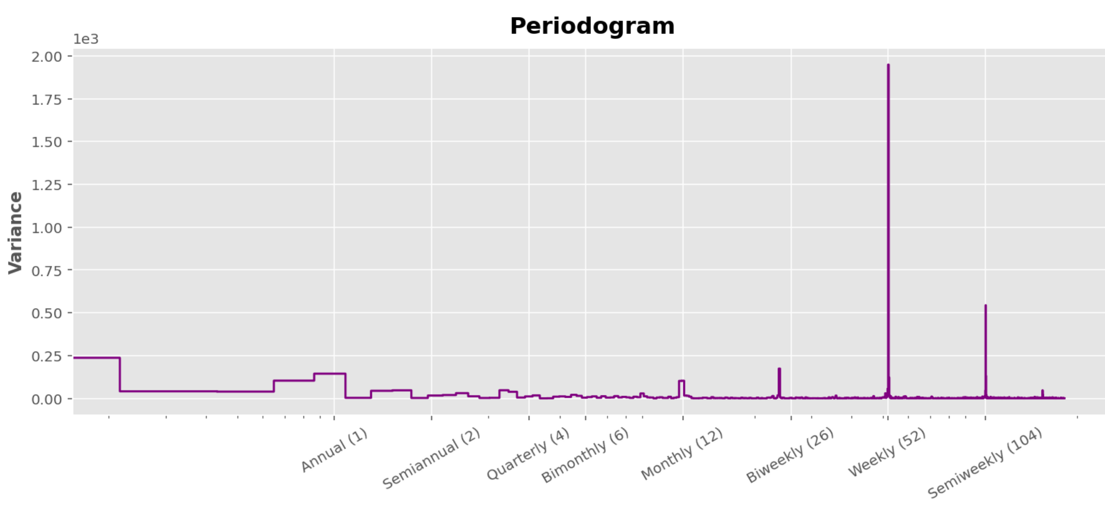
[129]:

```
ss_decomposition = seasonal_decompose(df, period=30)
estimated_obs = ss_decomposition.observed # additive series
estimated_trend = ss_decomposition.trend # upword trend
estimated_seasonal = ss_decomposition.seasonal # weekly seaonality
estimated_residual = ss_decomposition.resid
```

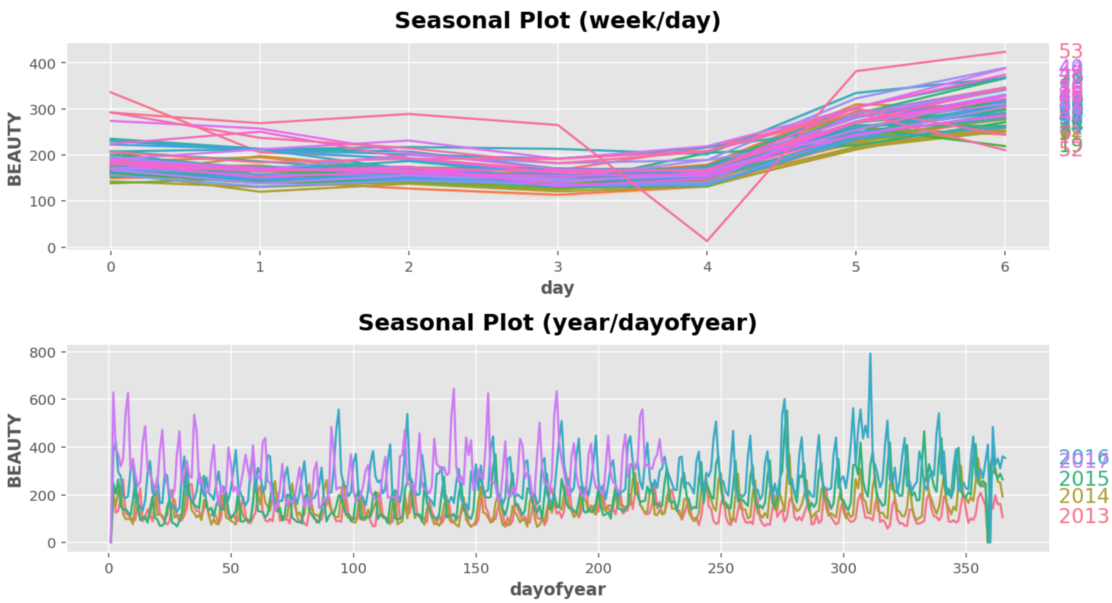
[130]:
```python
fig, axes = plt.subplots(4, 1, sharex=True, sharey=False)

axes[0].plot(estimated_obs, label='observation')
axes[0].legend(loc='upper left');

axes[1].plot(estimated_trend, label='Trend')
axes[1].legend(loc='upper left');

axes[2].plot(estimated_seasonal, label='Seasonality')
axes[2].legend(loc='upper left');

axes[3].plot(estimated_residual, label='Residuals')
axes[3].legend(loc='upper left');
```



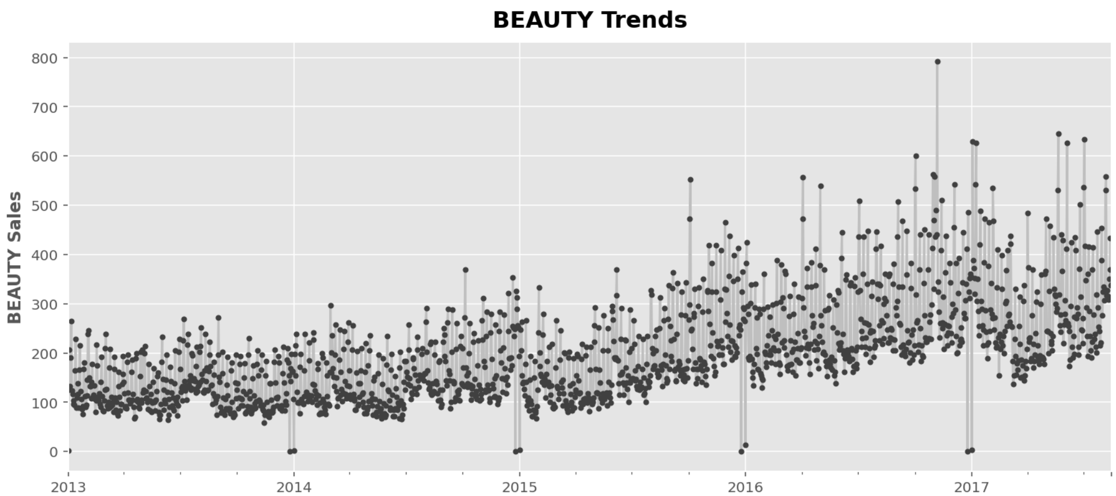
[32]:
```python
plot_periodogram(df['BEAUTY']); # strong weekly seasonality
```



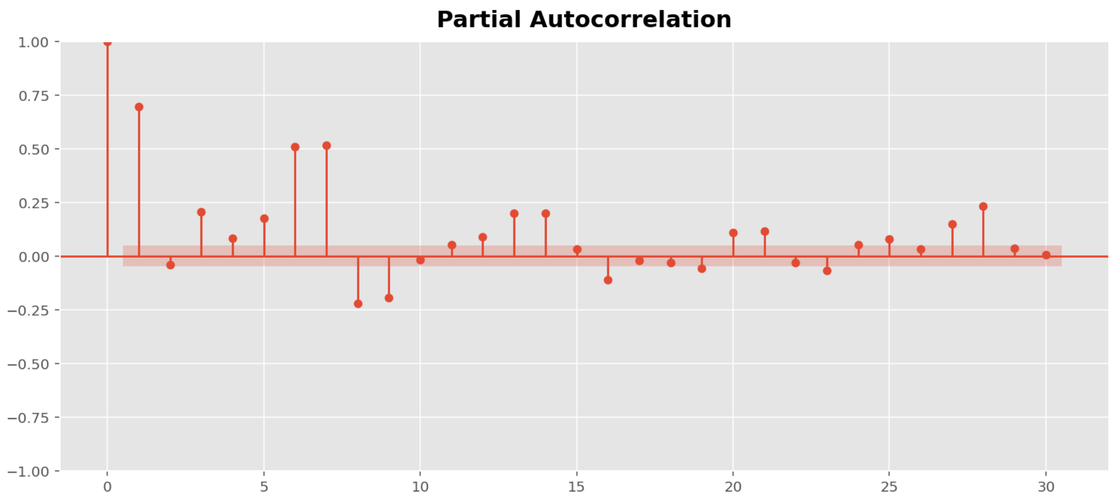
[33]:
```
X = df.copy()

# days within a week
X["day"] = X.index.dayofweek  # the x-axis (freq)
X["week"] = X.index.week  # the seasonal period (period)

# days within a year
X["dayofyear"] = X.index.dayofyear
X["year"] = X.index.year
fig, (ax0, ax1) = plt.subplots(2, 1, figsize=(11, 6))
seasonal_plot(X, y="BEAUTY", period="week", freq="day", ax=ax0)
seasonal_plot(X, y="BEAUTY", period="year", freq="dayofyear", ax=ax1);
```



[34]:
```
ax = df['BEAUTY'].plot(title='BEAUTY Trends', **plot_params)
_ = ax.set(ylabel="BEAUTY Sales")
```



[179]:
```python
_ = plot_lags(df['BEAUTY'], lags=30, nrows=5)
_ = plot_pacf(df['BEAUTY'], lags=30) # strong lag 1
```



[180]:
```
check = normaltest(df) # nonstationary
check
```

[180]:
```
NormaltestResult(statistic=masked_array(data=[36.43664462819144],
             mask=[False],
       fill_value=1e+20), pvalue=array([1.22428675e-08]))
```

[181]:
```
adf, pvalue, usedlag, nobs, critical_values, icbest = adfuller(df)

print("ADF: ", adf)
print("p-value:", pvalue) # nonstationary
```

```
ADF:  -1.849716339128221
p-value: 0.3560729196591387
```

[182]:
```
df = df.T
df.head()
```

[182]:
```
         2013-01-01  2013-01-02  2013-01-03  2013-01-04  2013-01-05  \
family
BEAUTY          4.0    5.337538    4.836282     4.89784    5.257495

         2013-01-06  2013-01-07  2013-01-08  2013-01-09  2013-01-10  …  \
family                                                               …
BEAUTY     5.583496    4.828314    4.762174     4.65396    4.574711  …

         2017-08-06  2017-08-07  2017-08-08  2017-08-09  2017-08-10  \
family
```

```
BEAUTY    6.326149    5.762051    5.796058    5.755742    5.736572

        2017-08-11  2017-08-12  2017-08-13  2017-08-14  2017-08-15
family
BEAUTY    5.863631    5.913503    6.073045    5.823046    5.828946

[1 rows x 1688 columns]
```

[194]:
```
X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=365, y_len=1,␣
 ↪test_loops=150)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[194]: ((1173, 365), (150, 365), (1173,), (150,))

[195]:
```
# Linear Regression as first model to compare

reg = Pipeline([('scaler', StandardScaler()), ('poly', PolynomialFeatures(1)),
                ('LinearRegression', LinearRegression())]) # Create a linear␣
 ↪regression object


reg.fit(X_train, y_train) # Fit it to the training data

# Create two predictions for the training and test sets
y_train_pred = reg.predict(X_train)
y_test_pred = reg.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='Regression')
```

```
             MAE  RMSE  Bias  MAE_pct  RMSE_pct  r2_score
Regression
Train       0.12  0.17   0.0     2.28      3.18      0.87
Test        0.16  0.20  -0.1     2.86      3.56      0.63
```

[196]:
```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=365, y_len=1,␣
 ↪test_loops=0) #use 252 for 1day, 253 for second day

reg = Pipeline([('scaler', StandardScaler()), ('poly', PolynomialFeatures(1)),
                ('LinearRegression', LinearRegression())]) # Create a linear␣
 ↪regression object

reg.fit(X_train,y_train) # Fit it to the training data
```

```
reg_forecast = pd.DataFrame(data=reg.predict(X_test), index=df.index)#,␣
↪columns=['21-02-2022', '22-02-2022'])
reg_forecast.head()
```

[196]:

```
              0
family
BEAUTY  6.06073
```

[197]:

```
# use Random Forest with default parameters

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=7, y_len=1,␣
↪test_loops=150)

forest = Pipeline([('scaler', StandardScaler()), ('Forest',␣
↪RandomForestRegressor())])

forest.fit(X_train, y_train)

y_train_pred = forest.predict(X_train)
y_test_pred = forest.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='Forest')
```

	MAE	RMSE	Bias	MAE_pct	RMSE_pct	r2_score
Forest						
Train	0.06	0.08	0.02	1.11	1.60	0.97
Test	0.15	0.21	0.96	2.66	3.66	0.61

[198]:

```
# prediction

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=7, y_len=1,␣
↪test_loops=0) #use 252 for 1day, 253 for second day

forest = Pipeline([('scaler', StandardScaler()), ('Forest',␣
↪RandomForestRegressor())])

forest.fit(X_train,y_train) # Fit it to the training data

forest_forecast = pd.DataFrame(data=forest.predict(X_test), index=df.index)#,␣
↪columns=['21-02-2022', '22-02-2022'])
forest_forecast.head()
```

[198]:

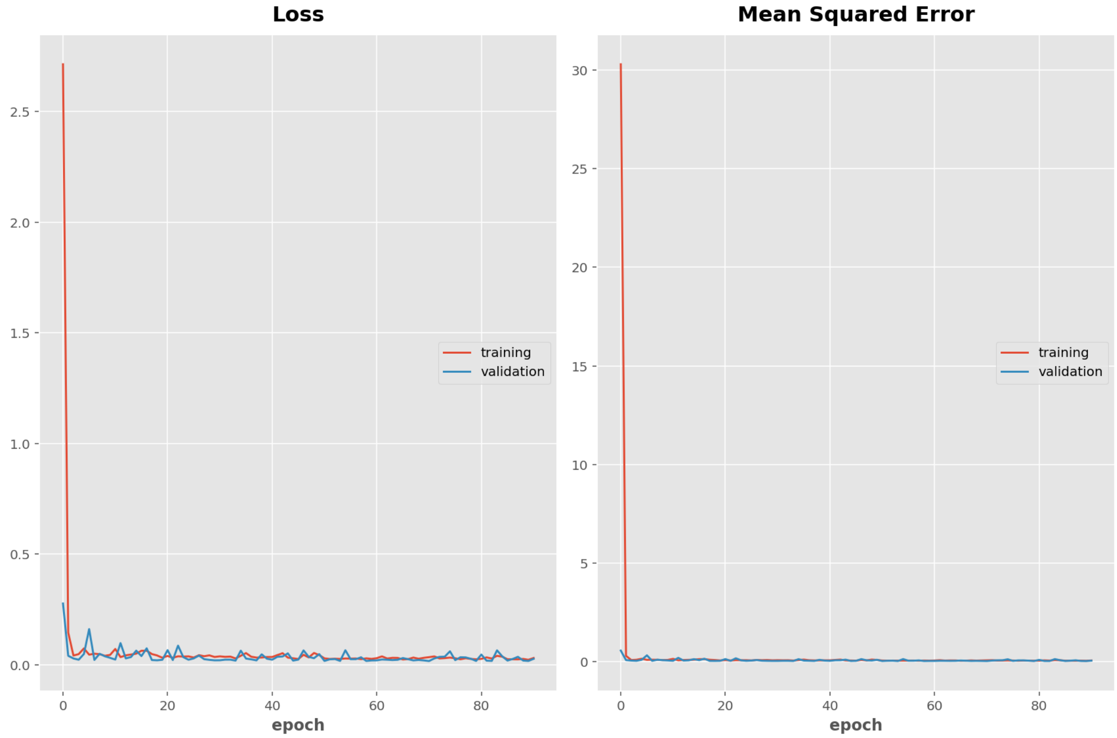
```
               0
family
BEAUTY  5.427848
```

[199]:
```python
x_len = 7
y_len = 1
n_features = 1

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=x_len,␣
 ↪y_len=y_len, test_loops=150)

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# reshape from [samples, timesteps] into [samples, timesteps, features]
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))
y_train = y_train.reshape(X_train.shape[0], y_len)
y_test = y_test.reshape(X_test.shape[0], y_len)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[199]: ((1531, 7, 1), (150, 7, 1), (1531, 1), (150, 1))

[200]:
```python
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)

callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0,␣
 ↪patience=20, verbose=0, mode='auto')

model = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=96,
                                                           kernel_size=5,
                                                           strides=1,
                                                           padding='causal',
                                                           activation='relu',
                                                           input_shape=(x_len,␣
 ↪n_features)),
                                    tf.keras.layers.LSTM(100,␣
 ↪return_sequences=True),
                                    tf.keras.layers.LSTM(100),
                                    tf.keras.layers.Dense(30),
                                    tf.keras.layers.Dense(10),
                                    tf.keras.layers.Dense(y_len),
                                    tf.keras.layers.Lambda(lambda x: x * 400)])


#model.compile(loss='mean_squared_error',optimizer='adam')

model.compile(loss=tf.keras.losses.Huber() ,optimizer='adam', metrics=['mse'])
```

```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=500,
                    callbacks=[PlotLossesKeras(), callback], verbose=1)
```




```
Loss
        training                 (min:    0.022, max:    2.714, cur:    0.030)
        validation               (min:    0.016, max:    0.277, cur:    0.026)
Mean Squared Error
        training                 (min:    0.045, max:   30.288, cur:    0.061)
        validation               (min:    0.033, max:    0.563, cur:    0.053)
48/48 [==============================] - 1s 24ms/step - loss: 0.0301 - mse:
0.0609 - val_loss: 0.0263 - val_mse: 0.0525
```

[201]:
```
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

kpi(y_train, y_train_pred, y_test, y_test_pred, name='LSTM')
```

```
        MAE  RMSE  Bias  MAE_pct  RMSE_pct  r2_score
LSTM
Train  0.17  0.22 -0.31     3.21      4.31      0.77
Test   0.17  0.23  2.02     3.02      4.07      0.51
```

[202]:
```
# Forecasting

x_len = 7
y_len = 1
n_features = 1

X_train, y_train, X_test, y_test = train_test_datasets(df, x_len=x_len,␣
↪y_len=y_len, test_loops=0)

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# reshape from [samples, timesteps] into [samples, timesteps, features]
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], n_features))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], n_features))
y_train = y_train.reshape(X_train.shape[0], y_len)
y_test = y_test.reshape(X_test.shape[0], y_len)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[202]: ((1681, 7, 1), (1, 7, 1), (1681, 1), (1, 1))

[203]:
```
tf.keras.backend.clear_session()
tf.random.set_seed(42)
np.random.seed(42)

#callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', min_delta=0,␣
↪patience=20, verbose=0, mode='auto')

model = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=96,
                                                           kernel_size=5,
                                                           strides=1,
                                                           padding='causal',
                                                           activation='relu',
                                                           input_shape=(x_len,␣
↪n_features)),
                                    tf.keras.layers.LSTM(100,␣
↪return_sequences=True),
                                    tf.keras.layers.LSTM(100),
                                    tf.keras.layers.Dense(30),
                                    tf.keras.layers.Dense(10),
                                    tf.keras.layers.Dense(y_len),
                                    tf.keras.layers.Lambda(lambda x: x * 400)])


#model.compile(loss='mean_squared_error',optimizer='adam')
```

```
model.compile(loss=tf.keras.losses.Huber() ,optimizer='adam', metrics=['mse'])

history = model.fit(X_train, y_train, epochs=100, verbose=0)
```

[204]:
```
model = pd.DataFrame(data=model.predict(X_test), index=df.index)#,␣
 ↪columns=['21-02-2022', '22-02-2022'])
model.head()
```

[204]:
```
               0
family
BEAUTY  5.438274
```

[ ]:
```

```